

Brain neurons as quantum computers: *in vivo* support of background physics

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Abstract

The question: whether quantum coherent states can sustain decoherence, heating and dissipation over time scales comparable to the dynamical timescales of the brain neurons, is actively discussed in the last years. Positive answer on this question is crucial, in particular, for consideration of brain neurons as quantum computers. This discussion was mainly based on theoretical arguments. In present paper nonlinear statistical properties of the Ventral Tegmental Area (VTA) of genetically depressive limbic brain are studied *in vivo* on the Flinders Sensitive Line of rats (FSL). VTA plays a key role in generation of pleasure and in development of psychological drug addiction. We found that the FSL VTA (dopaminergic) neuron signals exhibit multifractal properties for interspike frequencies on the scales where healthy VTA dopaminergic neurons exhibit bursting activity. For high moments the observed multifractal (generalized dimensions) spectrum coincides with the generalized dimensions spectrum calculated for a spectral measure of a *quantum* system (so-called kicked Harper model, actively used as a model of quantum chaos). This observation can be considered as a first experimental (*in vivo*) indication in the favour of the quantum (at least partially) nature of the brain neurons activity.

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1 Introduction

Many authors have argued that consciousness can be understood as a macro-quantum effect. In particular, Penrose [1] proposed that this takes place in microtubules, the ubiquitous hollow cylinders that among other things help cells maintain their shapes. It has been argued that microtubules can process information like a cellular automaton [2], and Penrose suggests that they operate as a quantum computer (see for a review [3]). On the other hand, a number of other authors have conjectured that environment-induced decoherence will rapidly destroy the quantum macrosuperpositions in the brain (see for instance [4],[5] and references therein). Indeed, the decoherence (as well as dissipation and heating) is a serious obstacle to all applications exploiting quantum coherence. Recently, considerable effort has been devoted to designing strategies able to counteract the undesired effects of the coupling with an external environment. Notable examples of these strategies in the field of quantum information are quantum error correction codes, error avoiding codes [6], and "parity kicks" method [7]. It is only beginning of such activity. It is quite possible that there exist still unknown strategies (and processes [8],[9]) which can eliminate in principle any undesired effect of the environment. Nature can utilize these strategies (processes) in neurons. Therefore, the simple calculations of the decoherence characteristic times (without taking into account such corrective possibilities) cannot be considered as a final verdict.

Methods of statistical physics are actively used for investigation of probabilistic properties of different neurons [10]-[20]. In the present paper we will study the data obtained *in vivo* for so-called Ventral Tegmental Area (VTA).

The Ventral Tegmental Area (VTA) is a midbrain nucleus consisting of the dopaminergic cells. VTA is known as a part of the limbic brain that corresponds to such high brain functions as cognition, learning, rewarding and emotional behavior. VTA plays a key role in the generation of pleasure and in development of psychological drug addiction. This area is also involved in control of the gonadal hormones [21].

The VTA dopaminergic cells fire in irregular manner with a mean rare rate between 0.5 to 10 Hz. Firing patterns of the healthy VTA dopaminergic cells include single spikes and short bursts containing 3-7 spikes. It is believed that the bursting manner of firing is probably pulled on by rewarding stimuli accepted from the glutamate neurons originating from prefrontal

cortex and hippocampus. Bursting activity of the normal VTA dopaminergic cells results in dopamine release in limbic brain. Dopamine release from VTA dopaminergic cells accompanies rewarding behavior. VTA dopaminergic cells are autoregulated via dopamine autoreceptors expressed on their somas. Additionally, activity of the VTA dopaminergic cells is regulated by serotonin, noradrenalin and acetylcholine.

Specific nonlinear properties of the VTA dopaminergic neurons are actively studied in recent years (see, for instance [13],[14] and references therein). Relationship between these properties and rewarding function of VTA is one of the topical problems. Therefore, comparative analysis of the nonlinear properties of the VTA signals generated by normal brains and ones generated by brains with genetically suppressed rewarding function of VTA seems to be of significant interest. For this purpose we use genetically defined rat model of depression (Flinders Sensitive Rat Line - FSL). Moreover, the genetically defined depression of the FSL rats (which suppresses the bursting activity of the dopaminergic neurons) and anaesthesia used in our experiment (see below) allows us extract a *background* signal generated by the dopaminergic neurons. Using universality of the background signal we will combine the signals taken from 5 single dopaminergic neurons (3 FSL rats) in order to obtain statistically representative data set (about 10000 spikes).

Usually, the time intervals, T , between neighboring spikes are used in order to study statistical properties of neuron signals. In the present paper we will use *inverse* interspike intervals (interspike frequencies) $\omega = T^{-1}$. While for probability density analysis there is no advantage in such choice, for a moment (multifractal) analysis the interspike frequencies turned out to be more informative (see below). In particular, we will show that the FSL VTA neuron signals exhibit multifractal properties for the interspike frequencies on the scales where the healthy VTA dopaminergic neurons exhibit bursting activity. The obtained generalized dimensions spectrum corresponds to the multifractal Bernoulli distribution and for the high moments this spectrum coincides with generalized dimensions spectrum calculated for a spectral measure of a *quantum* system (so-called kicked Harper model, actively used as a model of quantum chaos).

2 Experimental methods and materials

Male Sprague-Dawley rats were used in all experiments. Animals were anaesthetized with chloral hydrate (400 mg/kg., i.p.) and mounted in stereotaxic apparatus. The hole was drilled 4.2 mm. anterior from the interaural line and 1.0 mm lateral from the medial line. Extracellular recordings were processed by an electrode from VTA (8.0-8.6 mm dorsal from the lambda). The constant level of the anaesthesia was checked by EKG and chloral hydrate was added as necessary. Single unit recording was carried out by amplitude discrimination. Each recording from the single cell included at least 2000 spike events. After each experiment, the recording site was marked by a lesion caused by 15 mA DC for 10 sec. Brains were removed and stained with formalin before histological examination. Frozen sections were cut at 50 mm intervals. Microscopic examination of the sections was carried out aiming to verify that the electrode tip was placed in VTA.

3 Multifractal analysis

The interspike frequencies: $\omega(n) = T(n)^{-1}$, have obvious meaning in the case of simple periodic signals with constant period T . For a varying interspike interval $T(n)$ (where n is number of a spike in the spike series) meaning of $\omega(n)$ is not so clear, especially for a random-like $T(n)$. Therefore, it is useful to introduce a measure based on the interspike frequencies through a moving average

$$\omega_r = \frac{1}{r} \sum_{i=n}^{i=n+r} \omega(i) \quad (1)$$

This measure has a simple meaning of an average frequency for r spikes. Then, one can try to analyze this measure on existence of scaling properties using its moments:

$$\langle \omega_r^p \rangle \sim r^{-\mu_p} \quad (2)$$

Usually, normalized (dimensionless) moments $\langle \omega_r^p \rangle / \langle \omega_r \rangle^p$ are used for this purpose. In our case, however, we have $\mu_1 = 0$ directly from the definition. Therefore, the scaling exponents of the dimensionless moments (if existst) coincide with those of the moments (2). If the scaling exists one can use the exponents μ_p in order to calculate the generalized dimensions D_p [22]:

$$D_p = 1 - \frac{\mu_p}{p-1} \quad (3)$$

Figure 1 shows composite signal, $\omega(n)$, obtained from 5 singular dopaminergic (VTA) neurons of 3 FSL rats. Because the genetically defined depression suppresses the bursting activity of the dopaminergic neurons and because of the anaesthesia used in our experiment we can expect a *background* signal from the FSL dopaminergic neurons. In particular, we can expect an universality of the individual signals (i.e. a statistic similarity even between the signals obtained from the dopaminergic neurons which belong to different FSL rats). The combined signal contains of about 10000 data points. A few data points with relatively short (less than 0.01 s) interspike intervals were excluded from the combined data set (that is about 1% of the entire number of the data points).

Figure 2 shows the moments (2) calculated for the data set shown in figure 1, for $r = 3 - 13$. Log-log scales are chosen for comparison with the scaling equation (2). The straight lines (the best fit) are drawn to indicate scaling (2) in these scales.

Figure 3 shows the generalized dimensions D_p (3) (calculated using the exponents μ_p extracted from figure 2). The scales: D_p versus $\ln p/(p - 1)$ are chosen in figure 3 for comparison with the theoretical prediction for the multifractal Bernoulli distribution [23]:

$$D_p = D_\infty + c \frac{\ln p}{(p - 1)} \quad (4)$$

The straight line is drawn in figure 3 to indicate the multifractal Bernoulli distribution asymptotic (4) with multifractal specific heat $c \simeq 0.41$.

4 Discussion

The observed scaling interval: $r = 3 - 13$, covers the scales where bursting activity of the healthy dopaminergic neurons takes place (see Introduction). Analogous analysis of the control (healthy) rats did not reveal the multifractal behavior in this interval of scales. This observation can be interpreted as multifractality of the *background* signal of the dopaminergic (VTA) neurons. Moreover, clear tendency to the multifractal Bernoulli distribution, seen in figure 3 for the high moments (the straight line), indicates a fundamental underlying physics (kinetics) [23]. In order to proceed further in this direction we also show in figure 3 values of generalized dimensions calculated for a spectral measure of the kicked Harper model actively used as a model of

quantum chaos [24]. The kicked Harper model is obtained upon quantization of the following map:

$$p_{n+1} = p_n + K \sin(x_n), \quad x_{n+1} = x_n - L \sin(p_{n+1})$$

where K and L are some parameters. Canonical quantization thus leads to the one-period evolution operator

$$U_{L,K} = \exp[-i\frac{L}{h} \cos(h\nu)] \exp[-i\frac{K}{h} \cos(x)]$$

where operator $\nu = -i\partial/\partial x$, and $h/2\pi$ has to be considered as an effective Planck constant, playing a role similar to an incommensurability parameter in a quasi-periodic system. Quasi-energy eigenvalues and eigenvectors are determined by

$$U_{L,K}\psi_\omega = \exp[-2\pi i\omega] \psi_\omega$$

and, if we denote by ψ_0 the state in which the system is prepared at $t = 0$, the corresponding spectral measure will be indicated by $d\eta_{\psi_0}(\omega)$: its support is contained in the unit interval. The autocorrelation function is easily expressed in terms of the spectral measure as follows:

$$C(t) = \langle \psi_0 | U_{L,K} | \psi_0 \rangle = \int_0^1 d\eta_{\psi_0}(\omega) \exp[-2\pi i\omega t] \quad (5)$$

Information on the spectral measure is thus obtained by inversion of (5).

Multifractal analysis requires a sequence of approximations to the asymptotic spectral measure $\rho_{i(l)}$, where $\rho_{i(l)}$ is the probability attached to the i -th ball (of size l) covering the support of the spectral measure. The generalized dimensions is given by

$$D_p = \lim_{k \rightarrow \infty} \frac{1}{(p-1)} \frac{\log \chi_k(p)}{\log l_k}$$

where

$$\chi_k(p) = \sum_{j=1}^{N_k} \rho_j(l_k)^p, \quad l_k = 1/(2N_k + 1)$$

Phase diagram of the kicked Harper model is roughly divided into three regions [24], characterized, respectively, by a pure point spectrum (region A), a purely continuous spectrum (region B), and a mixed spectrum (region

C). Within region A scaling features were consistently not observed. Region B is, on the other side, characterized by good scaling properties, and a converging, non-trivial spectrum of generalized dimensions were obtained in [24]. The generalized dimensions for the parameters $K = 2$, $L = 5$ (with $N = 6400$) are shown as crosses in figure 3.

Reported above results can be considered as an indication of existence of a background dopaminergic neuron signal with universal multifractal properties for the scales where healthy dopaminergic neurons exhibit bursting behavior. This signal has multifractal Bernoulli distribution as high moments asymptotic that may be related to an underlying physics (kinetics) of mesoscopic systems [23]. In particular, the multifractal properties of a spectral measure of the kicked Harper model are in good quantitative correspondence with the observed multifractal properties of the dopaminergic neuron signals. The kicked Harper model is a prominent example of quasi-periodically driven quantum systems with a chaotic classical analogue, that also can be of significant interest for the discussion mentioned in Introduction.

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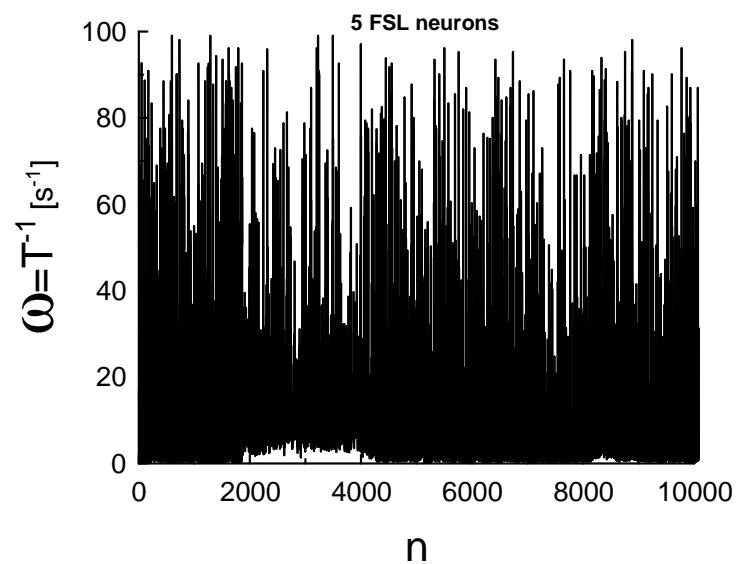


Figure 1: Composite signal, $\omega(n)$, obtained from 5 singular dopaminergic (VTA) neurons of 3 FSL rats.

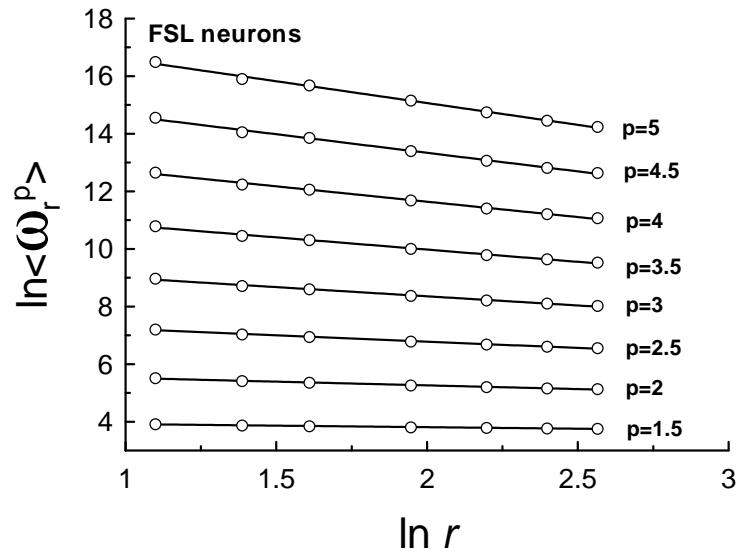


Figure 2: Logarithm of moments (2) versus $\ln r$ for the data set shown in figure 1, for $r = 3 - 13$. The straight lines (the best fit) are drawn to indicate scaling (2).

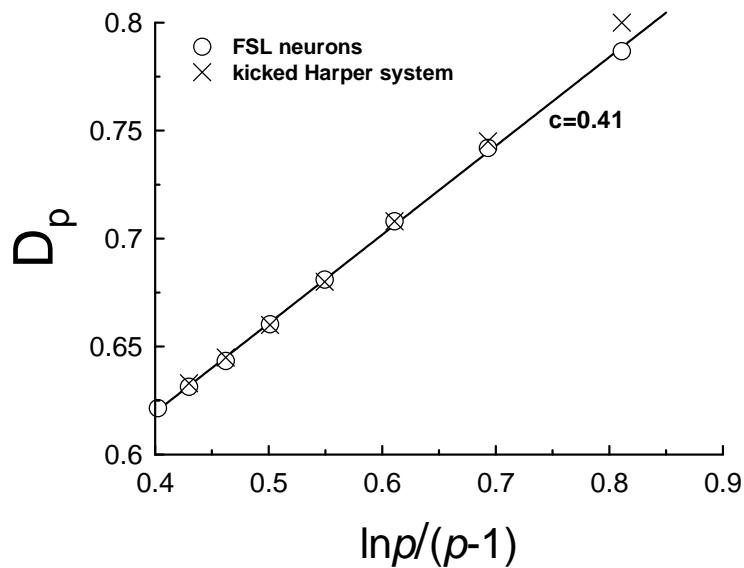


Figure 3: Generalized dimensions D_p versus $\ln p/(p-1)$ calculated using the exponents μ_p extracted from figure 2 (open circles) and for the kicked Harper model [24] (crosses). The straight line (the best fit) is drawn in figure 3 to indicate the multifractal Bernoulli distribution asymptotic (4).